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Testing of a Spectral-based Weed Sensor

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Summary:

A spectral-based weed sensor was tested in laboratory and in field. The effective sensing area of the sensor was determined by measuring sensor response when weeds were placed at different grid points in front of the sensor. When multiple weeds shared the effective sensing area of the sensor with soil, the weed classification rate was above 70%. The classification rate was below 50% for single weeds. Under field conditions, the weed classification rate reach 87%. Variations in sunlight did not affect the performance of the sensor significantly. The effect of shadows on the performance was significant.

Keywords: Optical sensor, Weed detection, Effective sensing area, Field test, Weed density, Precision agriculture

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Introduction

Site-specific herbicide application is an important component of modern precision agriculture. Detecting weeds in a crop field is a challenging task. With the advancement of computer technologies, machine vision has been identified as a possible solution for weed detection. Image-based weed sensors discriminate weeds from soil and crops using shape, texture, or color features. El-Faki et al. (1997) developed an image-based weed detection system using relative color indices formed by RGB gray levels. The system was less sensitive to canopy overlay, leaf orientation, camera focusing, and wind effect than systems based on plant shape and texture features. Burks et al. (1999) applied a color co-occurrence method (CCM) to develop texture statistics as input variables of a backpropagation (BP) neural-network for weed classification. Thirty-three unique statistic CCM texture inputs were used to achieve overall classification accuracy of 96.7%. An intelligent sensing and spraying system was developed by Tian et al. (2000). A real-time machine vision system was integrated with an automatic herbicide sprayer. The system classified weed based on infested zone (0.254 m by 0.34 m) rather than individual weeds. The overall accuracy of the sprayer was 100% in bare soil zones, 75% in weed-infested zones, and 47.8% in crop plant zones based on a weed-sensing algorithm using discrete wavelet transformation.

Optical weed sensors using spectral characteristics of plants in the visible and near-infrared (NIR) wavebands are another solution to fast and low-cost weed detection. Bargen et al. (1992) designed a red – NIR reflectance sensor to detect growing plants. Four wavelengths (two in the visible region, the other two in the NIR region) were selected for constructing the reflectance indices. The results provided a strong indication when a live plant is present within the sensor's field of view. Hummel and Yu (1998) reported their research on identifying and locating plant in the field using a spectral reflectance- based prototype WeedScanner system. They developed two algorithms to distinguish corn plant from weeds within specific size and density ranges. Biller (1998) used a commercial optoelectronic system "Detectspray" for weed detection and achieved 30%-70% reduction in herbicide use. Feyaerts et al. (1998) designed a spectral reflectance sensor using an imaging spectrograph. The results showed that, under controlled conditions, corn and sugar beet could be correctly classified against weeds with accuracies of 90% and 80%, respectively.

The advantages of optical sensors over machine-vision systems for weed detection include their low costs, simple system configurations, and high processing speeds. If a limited number of significant wavelengths can be identified, optical sensors may prove to be more practical for field implementation.

Wang et al. (1998,1999) studied spectral characteristics of stems and leaves of five crops and 30 weed species with spectral data collected using a spectrometer. Five significant wavelengths, at which the contrasts between major categories of object features were maximized, were selected. Color indices were developed based on reflectance of objects at these wavelengths. Classification models were established using the partial least-squares and the discriminant-analysis methods. Based on the classification model, an optical sensor was designed. Color indices were modified based on experimental data to be more illumination-insensitive. Laboratory tests showed that the sensor identified wheat, bare soil, and nine weed species as lumped to "weeds" with classification rates of 98.3%, 98.7%, and 64.3%, respectively. This paper reports results of further laboratory and field tests of this sensor. The objectives of these tests were:

1. to study the effective sensing area (ESA) of the sensor,
2. to study the capability of the sensor in detecting weeds at different weed densities,
3. to test the sensor under field conditions.

System Configuration

The integrated weed-detection system developed in this study consisted of weed sensors, a central control unit, a GPS unit, and sprayer units. The system block diagram is given in Figure 1.

The weed sensor consisted of an optical unit, a signal conditioning unit, an illumination unit, and a data acquisition unit (Wang et al., 1999). Design of the optical unit was based on the classification model developed by Wang et al. (1998). The sensor contained five phototransistors and five inexpensive, thin-film, color filters with passing bands approximately equal to selected wavelengths. An additional phototransistor without an optical filter was added to provide the reference light intensity.

Two types of data acquisition systems were used during the laboratory and field tests. A DAS 1801ST-DA data acquisition system (Keithley Instruments Inc.) installed in a 166MHz Pentium computer and the TestPoint software (Capital Equipment Corp., 1995) were employed for the ESA and weed-density tests in laboratory. The TestPoint program performed data collection and processing. It also displayed the signals and stored the data in files for further processing. For the field test, a CR23x datalogger (Campbell Scientific, Inc.) was used as the central control unit. It collected analog signals, performed classification, and sent control signals to the sprayer unit, and displayed the classification results on LEDs.

The sprayer unit consists of two pulse-width-modulated solenoid valves, a herbicide tank, an N-serve pump (John Blue Company), a sprayer boom, and two flat-fan nozzles. A GPS unit will be integrated into the system to measure the speed of tractor for nozzles control. The GPS unit is also expected to assist in developing weed maps based on the optical sensor measurement.

Experimental Procedure

The weed-density and ESA tests were conducted in laboratory in 1999. The field test was conducted in the early summer of 2000.

Weed-density test

Five weed species - field bindweed (*Convolvulus arvensis*), field pennycress (*Thlaspi arvense*), flixweed (*Descurainia sophia*), kochia (*Kochia scoparia*), redroot pigweed (*Amaranthus retroflexus*)- and wheat were planted separately in small containers in a greenhouse. These weed species are the major weed in Kansas wheat fields. Tests were conducted 21 days after the planting date. The diameter of the containers was 12.7 cm, and an average of 10 seeds were planted in each container. Thus, the plant density within the container was approximately 7.9 plants/dm^2. To test the sensor's response to weed density, weeds in each container were thinned to three density levels: half density, quarter density, and single plant, which corresponded to 4.0, 2.0, and 0.8 plant/dm^2, respectively. Tests were conducted at each density level. To create replications, two samples of each species were prepared at four density levels. Figure 2 shows a sample of redroot pigweed before and after thinning.

During the test, the sensor was mounted on a boom, which was installed in front of a test tractor. In order for the sensor to "see" both stems and leaves, the sensor was mounted at an inclination angle of 45° from the ground. The distance between the sensor and the plants was maintained at 40 cm. To avoid reflectance from surrounding objects, a 102 cm × 81.5 cm area outside the container was covered by soil. The entire test area was sheltered with black panels to make a "dark room" for the sensor. Samples of wheat and five weed species at four density levels (full, half, quarter, and single plant) and bare soil were tested in a random order. Each test was replicated using two samples. At first, the classifier was trained using samples of weed and wheat at the full density level and bare soil. Then, all samples were tested using the classifier. Classification rates were calculated for each individual sample.

ESA test

This experiment was to determine the area within which the sensor can correctly identify weeds. The testing apparatus included a wooden frame to support the boom, on which the weed sensor was mounted at an inclination angle of 45°, and a movable wooden platform (198 cm × 122 cm). The wooden platform was equipped with rollers so that it could move under the boom in any direction. A container of redroot pigweeds planted at a density level of 7 plants/dm^2 was situated at the center of the platform, which was set as the origin of a X-Y coordinate system. The sensor response was measured when the platform moved to 5.08 cm × 5.08 cm grid points within an area of 40.6 cm × 40.6 cm. In the area surrounding the origin of the coordinate system, the sensor responses were measures at half-grid points (2.54 cm × 2.54 cm). Four halogen-tungsten flood lamps with spherical reflectors were used to illuminate the platform. The light intensity was adjustable by a rheostat.

A DAS 1801ST-DA data acquisition system was used to collect data from the sensor. At each grid point, about 350 data points were taken within a 2-minute period under variable light intensities. The data taken from weed samples at half-grid points (2.54 cm × 2.54 cm) surrounding the origin and bare soil were used to train the classifier. The classifier was trained using the discriminant analysis (DA) procedure in SAS. The classifier was then employed to test the weed data taken at each grid point. The grid points at which the classification accuracy fell below 80% were considered outside of the sensor's ESA.

Field test

Two experimental plots at the Ashland Bottom Experiment Field of KSU were prepared for the field test in the early may of 2000. 'Jagger' hard red winter wheat was planted in these plots at a row spacing of 20 cm. The primary weeds in the field were Palmer amaranth (*Amaranthus palmeri*) and ivyleaf morningglory (*Ipomoea hederecea*). The wheat was at about the 3-leaf stage when the first testing was started and at the 5 leaf stage and tillering when the testing was concluded. Weed stages ranged from 2 leaf to 6 leaf stages during the testing. There also were some scattered grasses such as giant foxtail (*Setaria faberi*) and large crabgrass (*Digitaria sanguinalis*) in the test area, which would have ranged from about the 2 leaf stage to tillering stages during the test period.

Two sensors were mounted on the front boom of a testing tractor with an inclination angle of 45° from the ground, 53.7 cm above ground. The sensor spacing was 45.7 cm. A digital video camera was mounted directly above the two sensors to take images within the ESA of the sensors during the test (Figure 3). The clock of the video camera was adjusted to synchronize the clock of the datalogger so that an image frame acquired from the video tape could be matched against the ESA of the sensors at each point. Thus, the video images could be used as a reference to examine the correctness of the classification results. A Campbell Scientific CR23x datalogger was employed to collect data for training the classifier and to perform real-time classification to validate the classifier.

Twelve analog input channels of the datalogger were used to acquire test data from two weed sensors. The sampling rate used was 2 Hz. Training data were taken from two areas within the field. The first area had weed densities of greater than 0.5 plants/dm^2 (Figure 5). In the second plot, weed density was below 0.12 plant/dm^2 (Figure 6). The data were taken when the tractor moved forward at a ground speed of 2km/hr. The training data were then transferred to a laptop computer. Discriminant analysis was performed using the SAS software (SAS Institute Inc. 1993) to calculated coefficients for the classification model. These coefficients were then copied to a CR23x program and downloaded to the datalogger. Areas used for validating the classification model were chosen from the same general areas used for training. Weed densities within the validation areas were checked using the images taken by the digital camera.

At the beginning, the classifier was trained to differentiate three classes of objects: weeds, wheat, and soil. It was then found that the classification accuracy for weeds and wheat was influenced by the training data used for soil. The number of classes was then reduced to two: weed and wheat. A much higher classification rates were achieved with this change. Field-test results reported in this paper are the results derived using the two-class model.

Results and Discussion

Weed-density test

Results of the weed-density test are summarized in Tables 1 and 2. For the training data set, which included a total of 5,332 observations, the classifier trained for three classes (bare soil, weeds, and wheat) successfully classified 100% bare soil (175) and wheat (897) observations, which included wheat at all four density levels. For weeds at the full, half, and quarter densities, 58.7% of the observations were identified correctly as weeds at these density levels, and 12.9% were identified as single weed plants. Combining these two cases, 71.6% were identified successfully as weeds. The remaining 28.4% were misidentified as bare soil. Of the 457 observations for single weed plants, only 45.8% were classified correctly, and the remaining 54.2% were misclassified as bare soil. As the density of weeds was reduced, soil covered a larger portion of the sensor's ESA, and it became increasingly difficult for the sensor to identify the weeds.

ESA test

Figure 4 shows the classification accuracy achieved within the 40.6 cm × 40.6 cm testing area using classification model trained with data surrounding the center of the ESA. Within a circular area with a radius of 15.25 cm, the classification rate in general was above 80%. For this study, this area was defined as the ESA of the sensor.

From Figure 4, it can be found that the ESA defined throughout the experiment was not exactly centered at the origin of the X-Y plane, which was the measured center of the ESA. In the longitudinal direction (Y-axis), the ESA seemed to be slightly shifted towards the direction where the camera was located. In the lateral direction (X-axis), on the other hand, there seemed to be a shift of about 7.62 cm towards the right side of the sensor. Due to this shift, the falling edge of the 3-D classification accuracy map was not centered. This shift may be due to inaccurate geometry of the phototransistor and optical installation.

The ESA test was conducted at only one level of weed density. For different weed densities, the ESA defined may be different. The ESA also may be defined differently if the area used for training was different.

Field test

The field test was conducted during time spans between noon and 6:00pm in a cloudy day. The light intensity varied within a wide range. The test results showed that, using the related color indices (Wang et al., 1999), the classifier was quite insensitive to sunlight change. The classification results on the training and validation data sets were shown in

Table 3 and Table 4, respectively. Sensor 1 identified weeds and wheat with classification rates over 92% and 98% for the training area and 86% and 99% for the validation area, respectively. For Sensor 2, the classification rates were 100% and 97% for the training area and 94% and 97% for the validation area, respectively.

Although sunlight change did not significantly affect classification rates, the shadows of the sensor and tractor did have considerable effects on the classification accuracy. When sunlight came from the back of the tractor, shadows of the sensor frame covered a large area of sensor's ESA. As results, the classification rates declined considerably. Table 5 shows the classification rates derived in the area used for the validation when shadows covered most part of the ESA of Sensor 2.

Conclusions

1. Laboratory test results showed that the weed sensor had an effective sensing area of 30.5×30.5 cm^2.

2. When multiple weeds shared the sensor's effective sensing area with soil, the classifier identified the weeds with classification rates of 71.6% and 73.8% for the training and validation data sets, respectively. When only a single weed appeared on the soil background, less than 50% of the weeds were classified correctly. The remaining weeds were misclassified as bare soil. In either case, no misclassification was found between weeds and wheat.

3. Using field data for training, the sensor successfully detected weeds at densities of 0.5 plants/dm^2 or above with a classification rate of higher than 96.9%.

4. The variation in sunlight during field test did not affect the performance of the classifier significantly. However, shadows had considerable effect on the performance.

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Table 1 Classification results for the training data set at four plant densities

Class			To: Bare soil	Weeds: Wd_fhq	Weeds: Wd_sg	Wheat: Wh_fhq	Wheat: Wh_sg	Total
From	Bare soil		**175** **(100)**	0 0	0 0	0 0	0 0	175 (100)
	Weeds	wd_fhq	927 (28.4)	**1913** **(58.7)**	422 (12.9)	0 0	0 0	3262 (100)
		wd_sg	541 (54.2)	0 0	**457** **(45.8)**	0 0	0 0	998 (100)
	Wheat	wh_fhq	0 0	0 0	0 0	**723** **(100)**	0 0	723 (100)
		wh_sg	0 0	0 0	0 0	0 0	**174** **(100)**	174 (100)
Total			1643 (30.8)	1913 (35.9)	879 (16.5)	723 (13.6)	174 (3.3)	5332 (100)

Notes:

wd_fhq: weeds at full, half, and quarter densities
wd_sg: weeds at single-plant density
wh_fhq: wheat at full, half, and quarter densities
wh_sg: wheat at single-plant density
Numbers in parentheses are percentages

Table 2 Classification results for the validation data set at four plant densities

Class			To: Bare soil	Weeds: Wd_fhq	Weeds: Wd_sg	Wheat: Wh_fhq	Wheat: Wh_sg	Total
From	Bare soil		**207** **(100)**	0 0	0 0	0 0	0 0	207 (100)
	Weeds	Wd_fhq	922 (26.2)	**2296** **(65.2)**	303 (8.6)	0 0	0 0	3521 (100)
		Wd_sg	605 (58.9)	0 0	**423** **(41.2)**	0 0	0 0	1028 (100)
	Wheat	Wh_fhq	169 (30.1)	0 0	0 0	**392** **(69.9)**	0 0	561 (100)
		Wh_sg	169 (100)	0 0	0 0	0 0	**0** **0**	169 (100)
Total			2072 (37.8)	2296 (41.9)	726 (13.2)	392 (7.2)	0 0	5486 (100)

Notes:

wd_fhq: weeds at full, half, and quarter densities
wd_sg: weeds at single-plant density
wh_fhq: wheat at full, half, and quarter densities
wh_sg: wheat at single-plant density
Numbers in parentheses are percentages

Table 3. Classification rates of the sensors derived on the areas used for training

Variety	Sensor 1		Sensor 2	
	Weed	Wheat	Weed	Wheat
Weed	**92.12%**	7.88%	**100%**	0
Wheat	1.85%	**98.15%**	2.15%	**97.85%**

Table 4. Classification rates of the sensors derived on the areas used for validation

Variety	Sensor 1		Sensor 2	
	Weed	Wheat	Weed	Wheat
Weed	**86.89%**	13.11%	**94.66%**	5.34%
Wheat	0.98%	**99.02%**	2.2%	**97.8%**

Table 5 Effect of shadows on the classification results

Variety	Sensor 1		Sensor 2	
	Weed	Wheat	Weed	Wheat
Weed	**97.24%**	2.76%	**61.6%**	38.4
Wheat	20.14%	**79.59%**	46.65%	**53.4%**

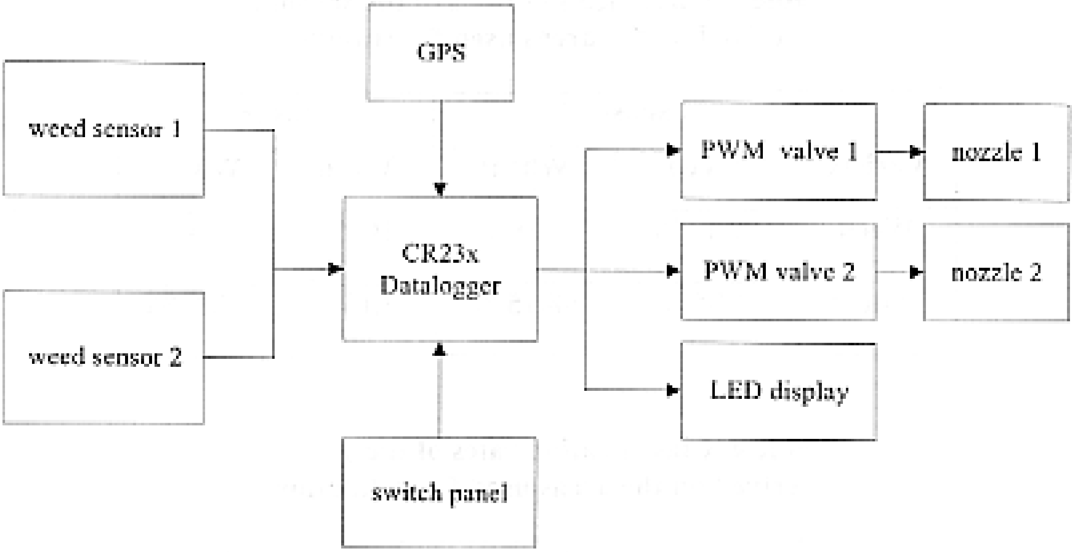

Figure 1. System block diagram

Figure 2. Redroot pigweed samples at different density level
(a) full (7.9 weed/dm^2) **(b) half (4.0 weeds/dm^2)**
(c) quarter (2.0 weeds/dm^2)
(d) single-plant (0.8 weeds/dm^2)

Figure 3. The testing tractor: the sensors were mounted on the front boom; the olenoid valves and nozzles were mounted on the rear boom; the data logger was installed in front of the operator; and the digital video camera faced ground to provide reference images.

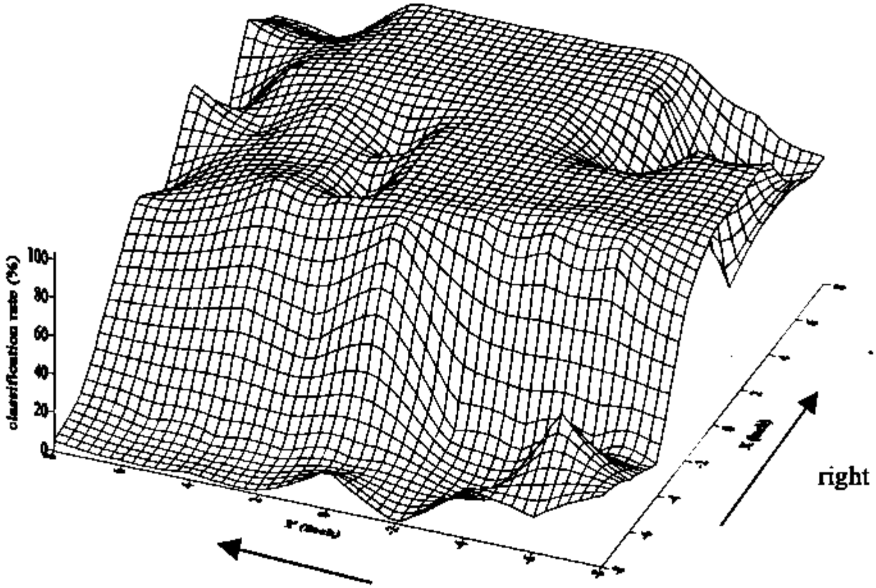

Figure 4. Classification accuracy measured when weeds were positioned at different locations in front of the sensor. The origin of the X-Y plane was the estimated center of the effective sensing area

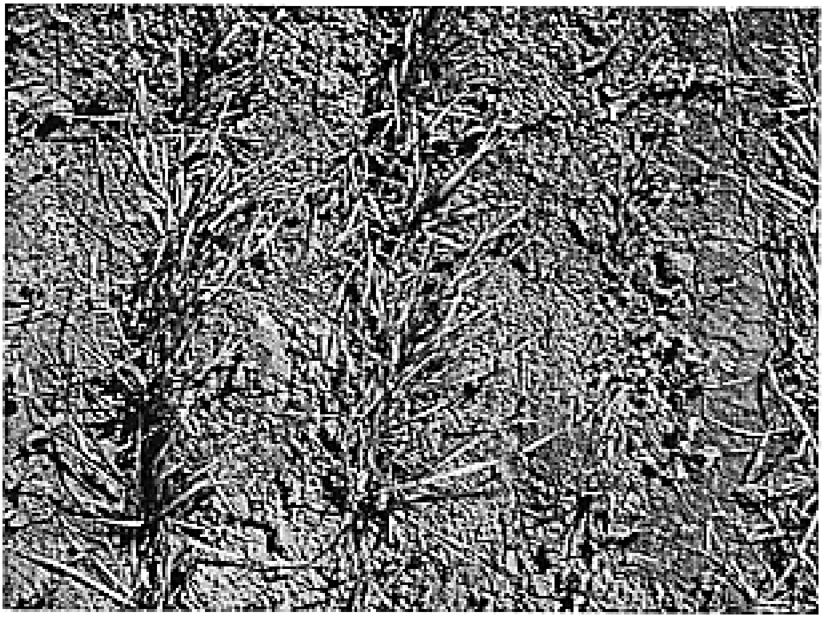

Figure 5. Image of an area used to acquire the "weed" data to train the classifier. Weed density in this area was at the lower threshold for "weed" (0.5 plants/dm^2)

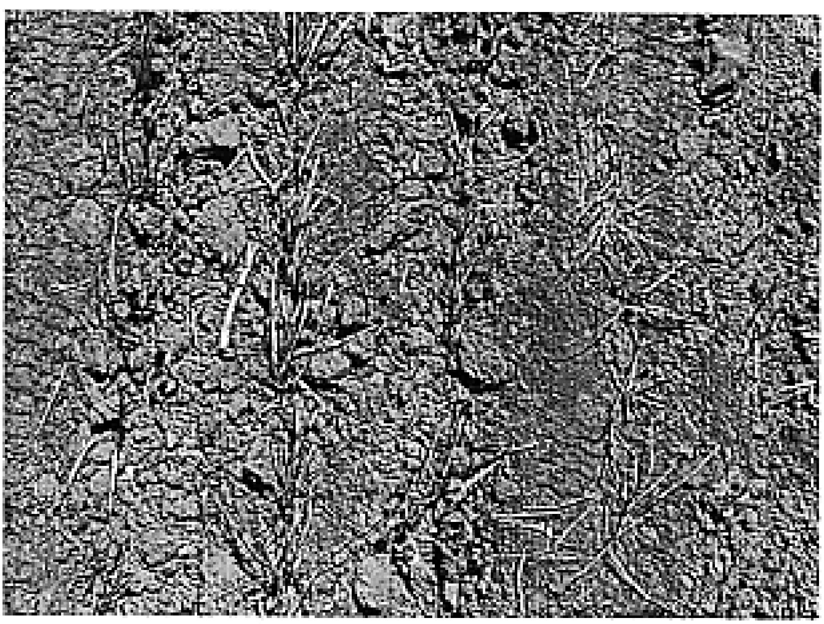

Figure 6. Image of an area used to acquire the "wheat" data to train the classifier. Weed density in this area was at the upper threshold for "wheat" (0.12 plants/dm^2)